Towards Optimal Snow Information from Space: A Synthetic Comparison of Observation Constellation Configurations

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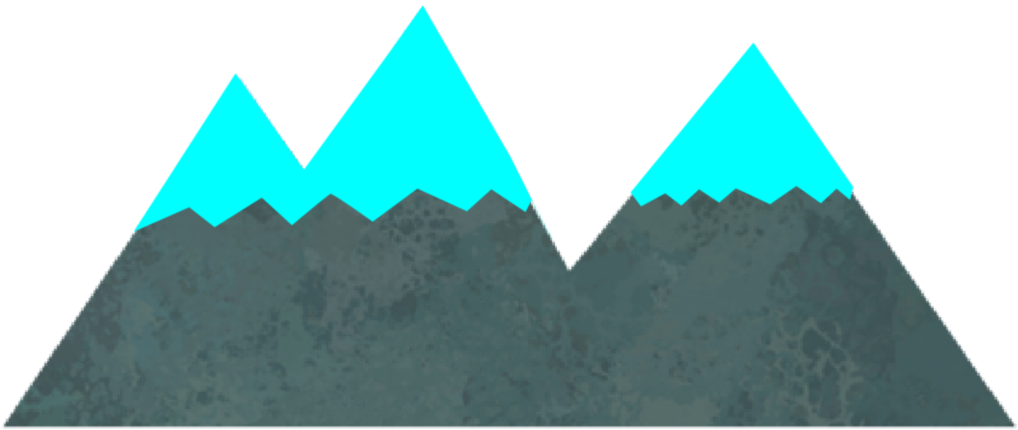
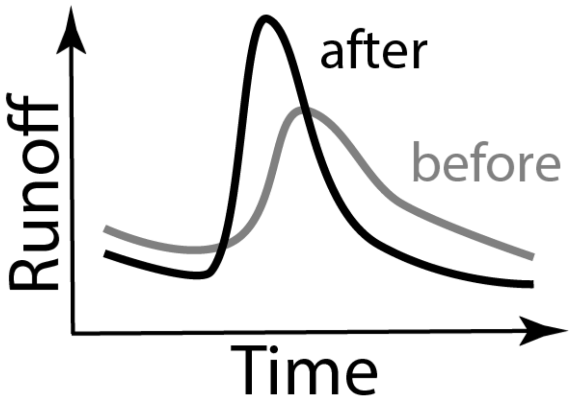
Importance of Snow

- Snow is a **significant contributor** to terrestrial freshwater supply
  - Up to 80% of runoff in some Western states
- Vital resource for **>1 billion people** worldwide
  - Not exactly sure **how much snow** is out there
  - **Difficult to measure**; significant uncertainty;
- Global warming → rising snow line
  - **reduced** virtual reservoir; **accelerated** hydrologic cycle;





NASA Decadal Survey

- Global warming → rising snow line → **reduced virtual reservoir**
- Goal is to improve snow mass estimation at regional / continental scales
  - **No dedicated snow mission**
  - **Water security** → food+energy security → **national security**

TABLE S.1 Science and Applications Priorities for the Decade 2017-2027

Science and Applications Area	Science and Applications Questions Addressed by **MOST IMPORTANT** Objectives
Coupling of the Water and Energy Cycles	**(H-1)** How is the water cycle changing? Are changes in evapotranspiration and precipitation accelerating, with greater rates of evapotranspiration and thereby precipitation, and how are these changes expressed in the space-time distribution of rainfall, snowfall, evapotranspiration, and the frequency and magnitude of extremes such as droughts and floods? **(H-2)** How do anthropogenic changes in climate, land use, water use, and water storage interact and modify the water and energy cycles locally, regionally and globally and what are the short- and long-term consequences?

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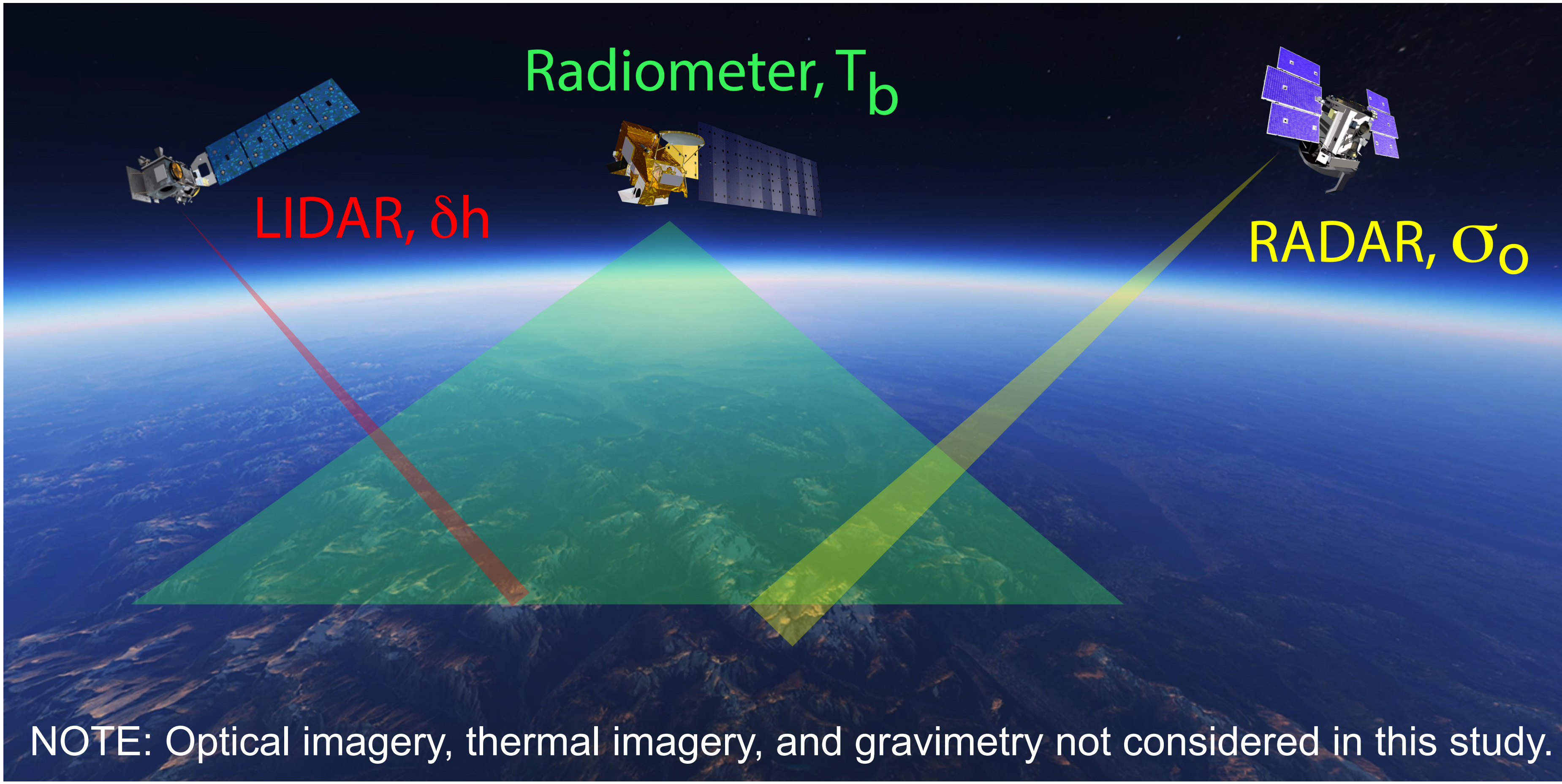
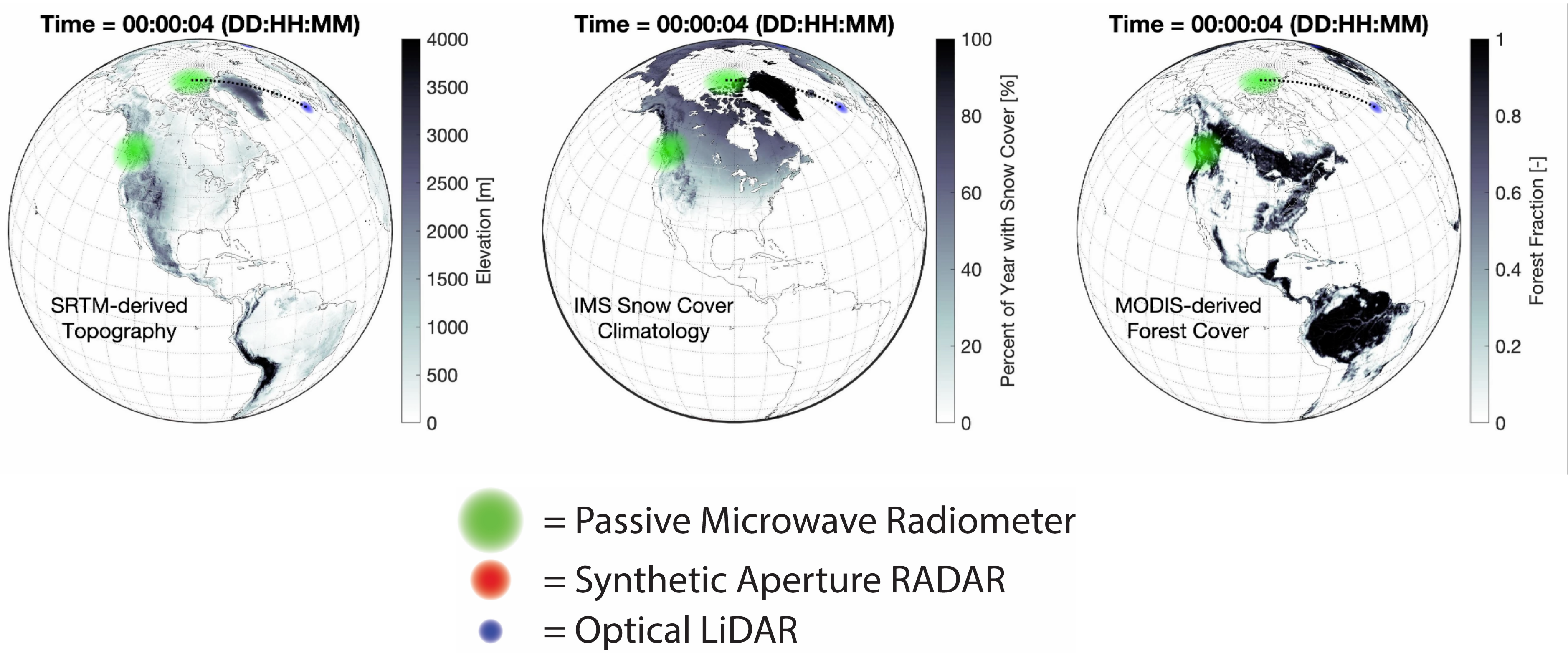
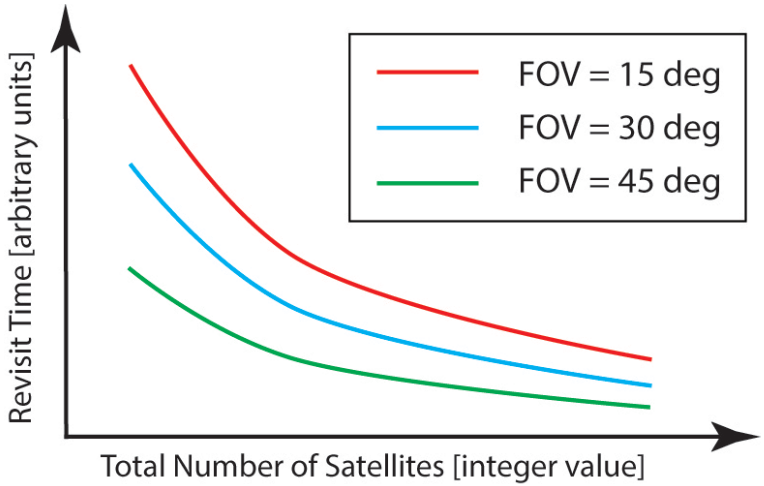
Satellite-derived Snow "Information"

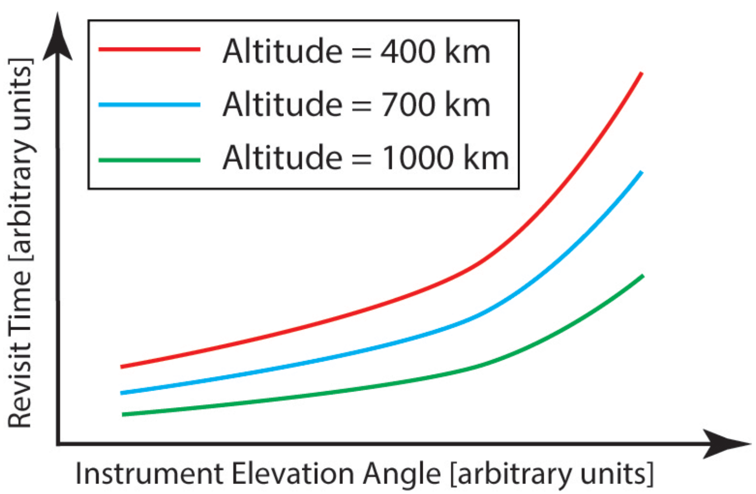


Multi-dimensional Trade Space



Trade-off Space: Coverage vs. Resolution





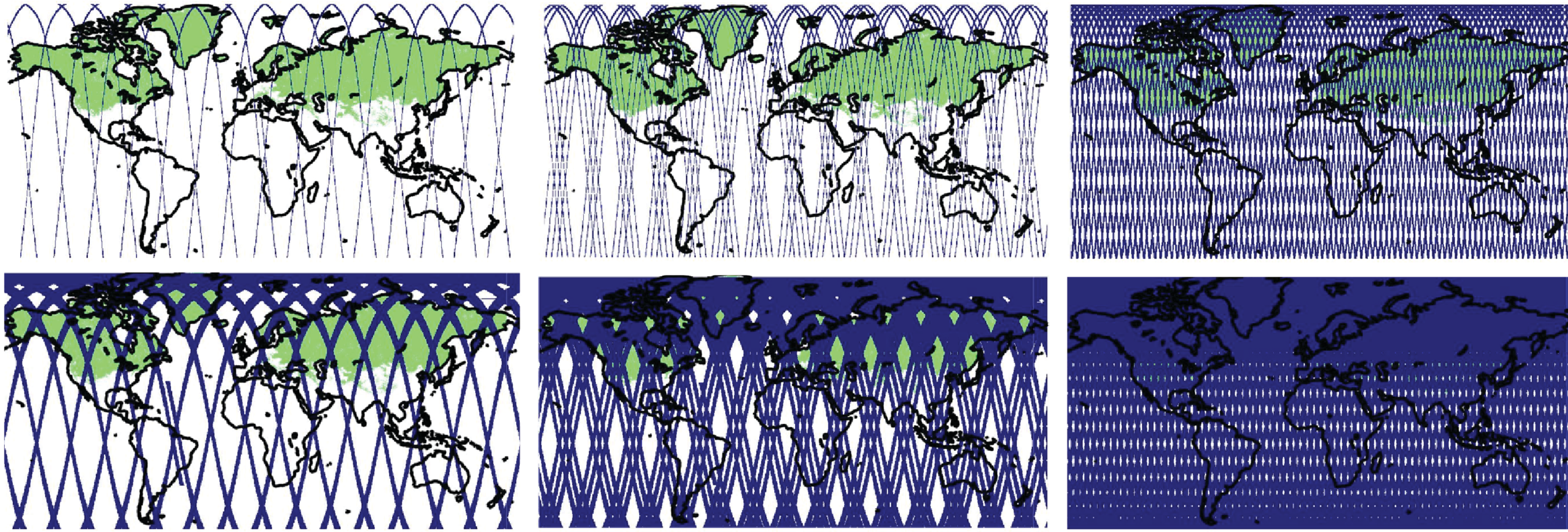
- Explore **trade-off** between engineering and science
  - Field-of-View (FOV)?
  - Platform altitude?
  - Repeat cycle?
  - Single platform vs. constellation?
  - Orbital configuration(s)?
- Tradespace Analysis Tool for Constellations (**TAT-C**)
  - *Le Moigne et al. [2016]*
- How do we get the most **scientific bang** for our buck?

Trade-off Space: Swath Width vs. Coverage

1-day Coverage | 3-day Coverage | 30-day Coverage

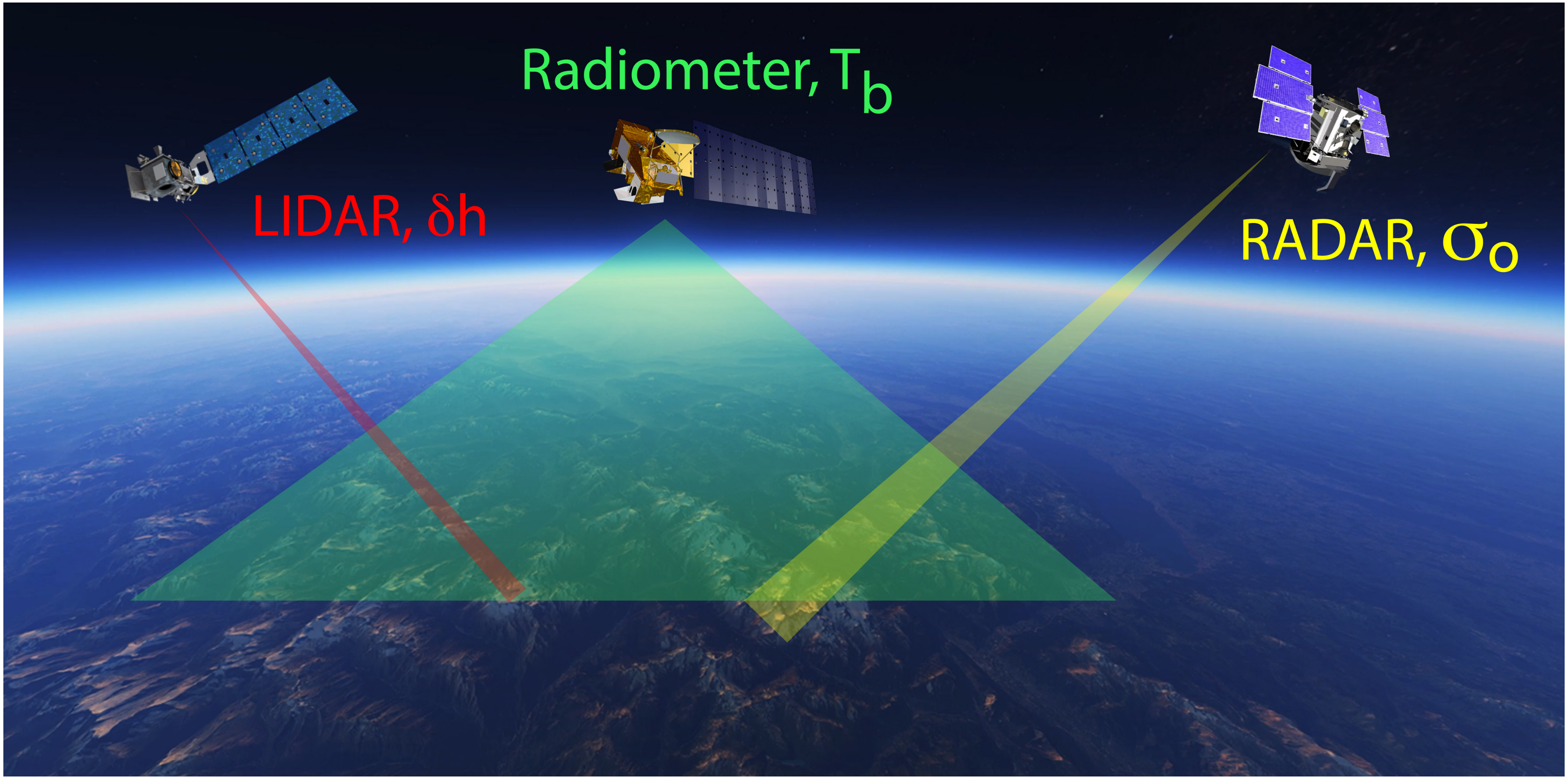
Wide Swath LiDAR

C-band SAR



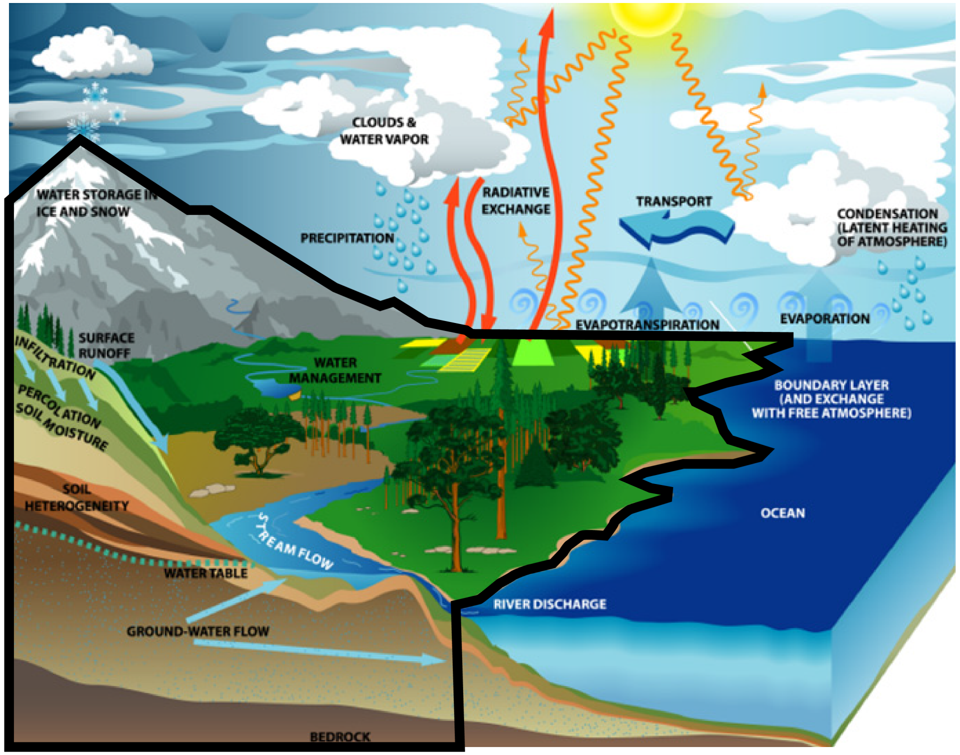
Sensor	1-day (Snow / Land+Ocean)	3-day (Snow / Land+Ocean)	30-day (Snow / Land+Ocean)
Wide Swath LiDAR	5.4% / 3.9%	15% / 11%	55% / 55%
C-band SAR	40% / 28%	79% / 65%	96% / 91%
Passive MW Radiometer	98% / 89%	>99% / 99%	>99% / 99%

Geophysical to Observational Space



NASA Land Information System (LIS)

- Models **land surface processes** (including snow)
- Integrates satellite-based **observational data** products with land surface **modeling and data assimilation techniques**



Kumar et al. (2006), Land Information System: An interoperable framework for high resolution land surface modeling, Environmental Modeling and Software

Research Objectives

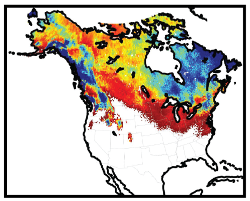
Science and mission planning questions

1) What observational records are needed (in space and time) to maximize terrestrial snow experimental utility?
2) How might observations be coordinated (in space and time) to maximize this utility?
3) What is the additional utility associated with an additional observation?
4) How can future mission costs be minimized while ensuring Science requirements are fulfilled?

Observing System Simulation Experiment (OSSE)

Nature Run

Snow Depth & SWE over North America

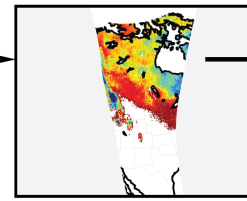


LIS + MERRA2
- model-based representation
- best estimate

TAT-C

Permutation of Orbit(s) + Sensor(s)

Sub-sample in space / time

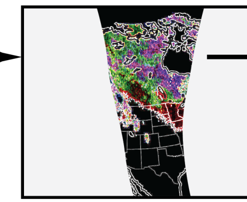


- includes cost estimate and risk analysis

Machine Learning "Emulators"

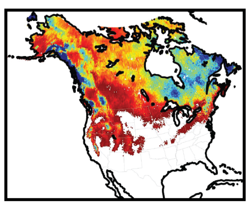
Synthetic Obs.

T_b, σ_o, and δh Operators



- inject known observation error

LIS Open Loop



LIS + GLDAS
- apply representative B.C. error
- no assimilation (a.k.a., Open Loop)
- with assimilation (merge with observations from suite of sensors)

LIS Assimilation

Open Loop (i.e., no assimilation)

Data Assimilation (merge w/ synthetic obs.)

Land Validation Toolkit (LVT)

Benchmark evaluation against "Nature Run"

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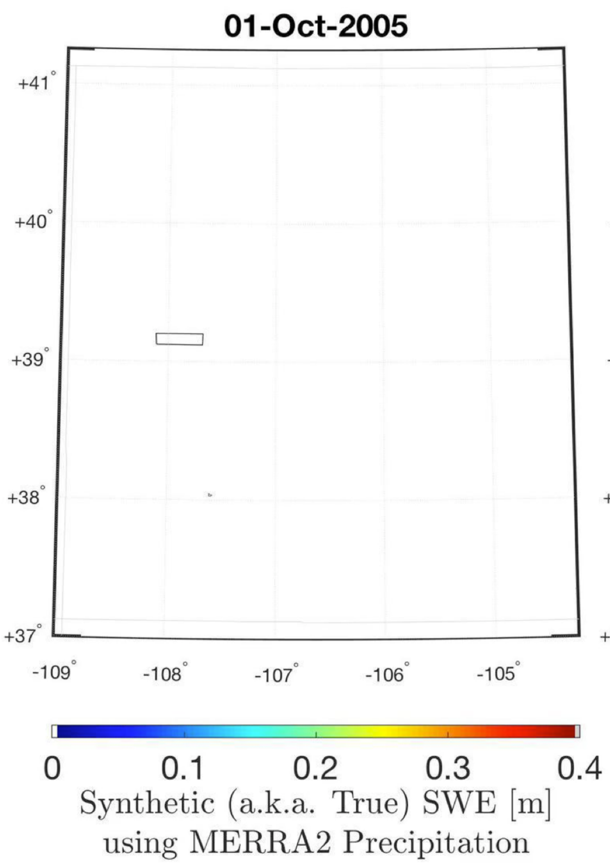
Synthetic Snow Depth Retrieval Results

“Truth”



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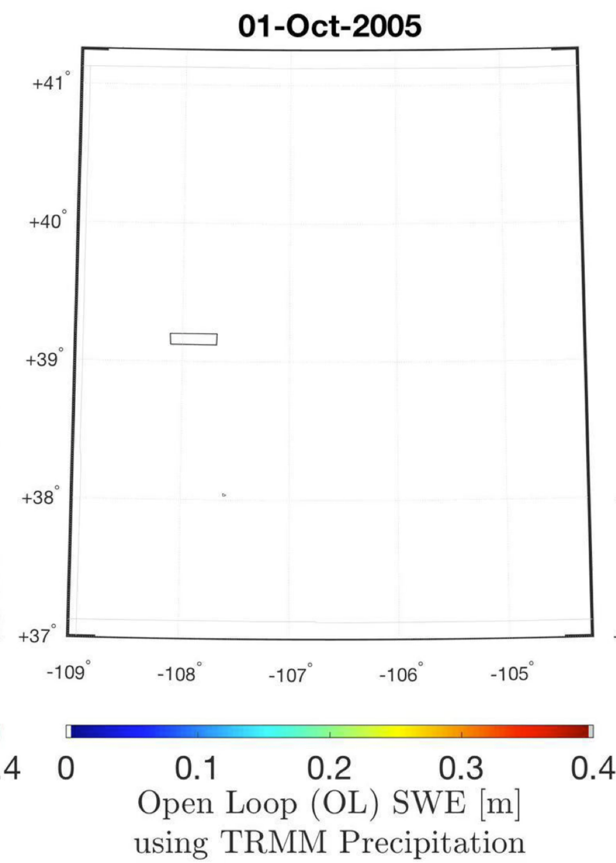

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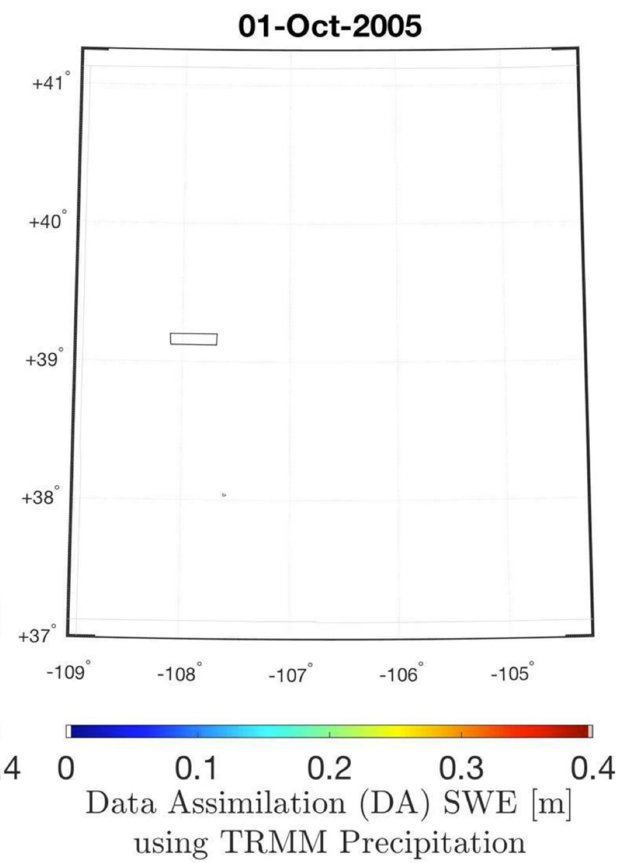

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Research Summary

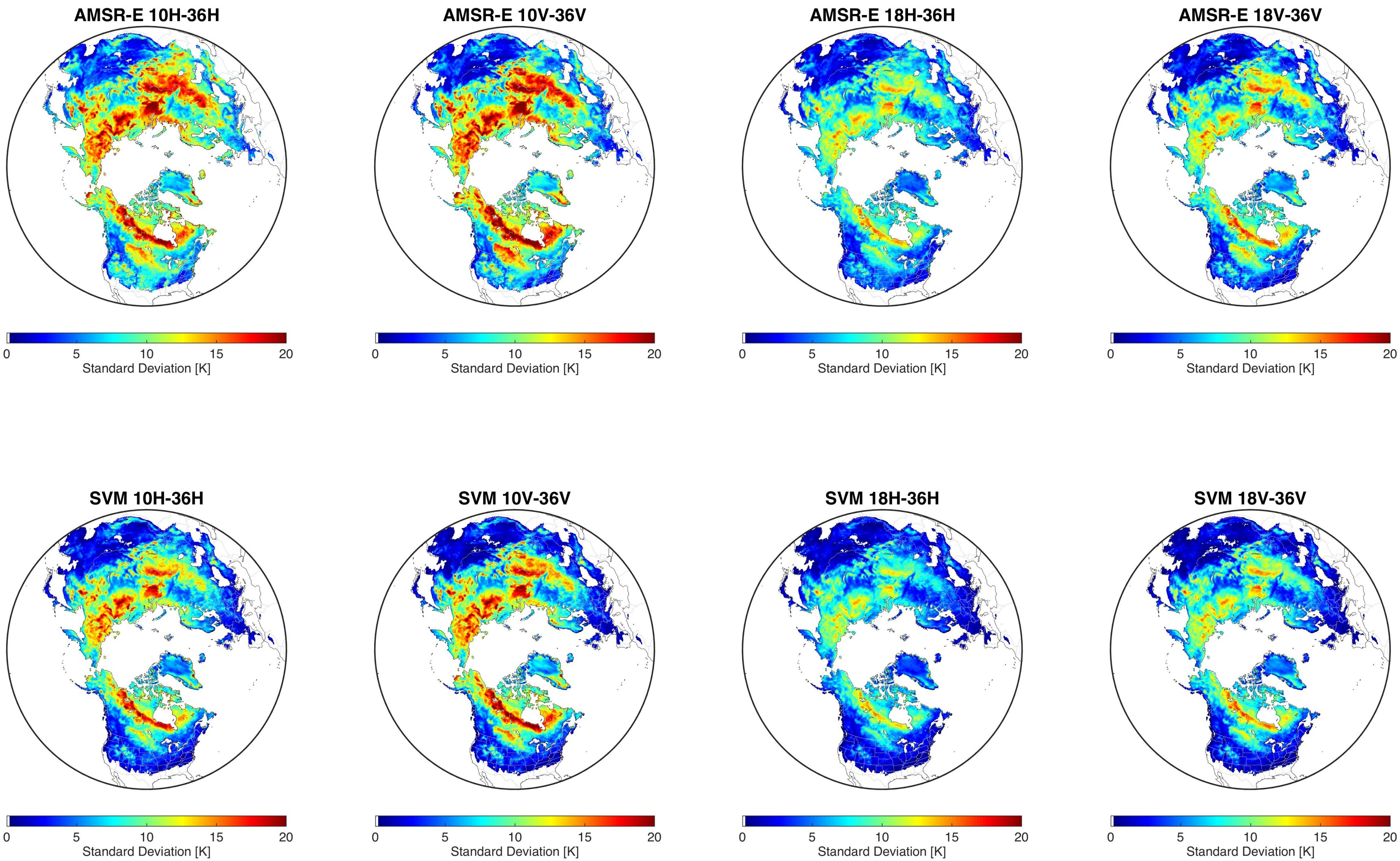
- Global snow mission will require **evidence of achievable science** via OSSE . . . or some other means
- NASA LIS provides **“nature run”** plus assimilation framework
- TAT-C provides **spatiotemporal sub-sampling** of observations, including **cost estimates and risk assessments**
- Machine learning **maps model state(s) into observation space** (i.e., T_b and σ_0)
- Snow **OSSE is on-going** . . . production runs in process.

Thank You!

Questions and/or comments?

Extra Slides

Spatiotemporal Variability



SVM Mathematical Framework (1 of 2)

For parameters $C > 0$ and $\varepsilon > 0$, the **standard (primal)** form is:

$$\begin{array}{ll} \underset{\mathbf{w},\, \delta,\, \boldsymbol{\xi},\, \boldsymbol{\xi}^*}{\text{minimize}} & \frac{1}{2}\langle \mathbf{w} \cdot \mathbf{w} \rangle + C \sum_{i=1}^{m} (\xi_i + \xi_i^*) \\ \text{subject to} & \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle + \delta - z_i \leq \varepsilon + \xi_i \\ & z_i - \langle \mathbf{w} \cdot \phi(\mathbf{x}_i) \rangle - \delta \leq \varepsilon + \xi_i^* \\ & \xi_i, \xi_i^* \geq 0, i = 1, 2, \ldots, m. \end{array}$$

where m is the available number of T_b measurements in time (for a given location in space), z_i is a T_b measurement at time i, and $\boldsymbol{\xi}$ and $\boldsymbol{\xi}^*$ are slack variables.

SVM Mathematical Framework (2 of 2)

Primal optimization is commonly solved in **dual form** as:

$$\begin{aligned}
\underset{\alpha_i\,,\,\alpha_i^*}{\text{minimize}} \quad & \frac{1}{2}\sum_{i,j=1}^{m}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)\langle\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)\rangle \\
& +\varepsilon\sum_{i=1}^{m}\left(\alpha_i+\alpha_i^*\right)-\sum_{i=1}^{m}z_i\left(\alpha_i-\alpha_i^*\right) \\
\text{subject to} \quad & \sum_{i=1}^{m}\left(\alpha_i-\alpha_i^*\right)=0, \\
& \alpha_i\,,\,\alpha_i^*\in[0\,,\,C]\,,\; i=1,2,\ldots,m
\end{aligned}$$

where α_i and α_i^* are Lagrangian multipliers, $\langle\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j)\rangle$ is the inner dot product of $\phi(\mathbf{x}_i)$ and $\phi(\mathbf{x}_j)$, ε is the specified error tolerance, and C is a positive constant that dictates a penalized loss during training.

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